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The Influence of Adaptive AI Learning systems on Cognitive Load and Academic persistence

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ABSTRACT

The present study examined the correlation between the use of adaptive AI learning systems, the cognitive load of university students in Punjab, Pakistan, and persistence in terms of academics. Quantitative research design and information gathered among 300 undergraduate and graduate learners that have completed one or more courses with the adaptive AI platform was employed. Women were represented in the different demographics through stratified random sampling. Statistical methods to analyze the data were used to understand the relationships, predictive effects and group differences. The outcomes indicated a strong negative correlation between adaptive use of AI and cognitive load, which means the AI-based learning tools assist with a reduction in the mental effort required in the learning process. Regression analysis indicated that adaptive AI use also had a significant effect on the prediction of academic persistence that implies that AI learning assistance provided on a personalized level encourages students to endure in their studies. Independent t test showed that academically surveyed students whose AI usage was high recorded a far much significant resulting academic persistence as opposed to the surveyed students whose usage of AI was low. Such results agree with other studies which conclude on the importance of technology enhanced learning in enhancing education. The study summarizes that the role of adaptive AI learning system is a potentially valuable guide to establishing enjoyable, individualized and effective learning experiences. The next studies should incorporate long-term impact on AI integration and bring the ethical aspect to it to the fullest in terms of maximizing the good and ensuring equity and fairness.

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1. Introduction

Over the past few years, the use of Artificial Intelligence (AI) in the education sector has dramatically transformed the learning process of the students and teaching method of the educators. Adaptive AI learning systems will alter the amount of time taken and the level of content and difficulty that each student requires. Based on the interactions with the students, these systems can classify data and offer individual feedback and on any resources they can suggest and generate learning pathways that suit the strengths and weaknesses of the learners (Holmes, 2020).In this manner, they want to minimize the time they spend in unnecessary thinking in order to learn as efficiently as possible. Classrooms are not the only area going through a revolution with the increasing application of adaptive AI tools since online and distance learning are also facing changes. Since education is increasingly digitized, it is necessary to know how such systems affect the mental workload, or cerebral load, as well as the desire to pursue learning further, or academic persistence, of students (Chen et al., 2025).This relationship is worth studying so that educators and policymakers can make decisions regarding the use of AI in enhancing the education achievement of diverse learners.

Cognitive load is the name they have given to the amount of mental work that a student brings to bear upon a fresh information reception. In cases where the cognitive load is high, the students are overwhelmed leading to the non-occurrence of the learning and possible demoralization to continue with the studies (Hussain et al., 2025).Reflective load can be facilitated through use of adaptive AI learning systems that break down a complex concept into minor tasks; provide information on how to do something in a step-by-step manner; and adjust the task difficulty level, as required. At the example of the student who does not know something, the system could be used to slow down; the explanation could be simplified, and with high-achievers, more advanced or complex material revealed (Khalil et al., 2024).This personal attention allows the learners to focus on the learning and not to focus on irrelevant distraction or confusion. Because of the use of cognitive load management in the form of the adaptive AI, it is conceivable that this new mechanism on its own terms would make learning process much more satisfying and fruitful, and this might help both in the short run performance, and the longer term recall of the information in question(Strielkowski et al., 2025). This would be quite necessary since it would be necessary to consider the design of such systems and their consequences in different levels of academic work.

Academic persistence can be defined as the student who has the capacity and motivation to maintain the process of attaining educational goals in spite of adversity or obstacles. The elements such as motivation, self-confidence, and perceived progress are also influential in persistence (Afifi et al., 2023).Persistence Persistent learning can be supported by an adaptive AI learning system that provides constant feedback to students, encourages them by praising minor success, and provides them with achievable goals. This is because such constant encouragement can fortify their faith in their capabilities and keep them motivated in the long term (Zheng et al., 2023).Learners will have high chances of staying focused in schools when they notice that their effort is bearing fruits to growth. Moreover, adaptive AI systems will be able to identify indicators of lack of engagement early on. These may include a lack of response, in the case of interactive systems, or a decline in the frequency of responses or interactions. Accordingly, such systems can intervene with special instructions to bring the learner back to the task. It can be especially beneficial to those at-risk students who could have dropped out or become disinterested in other remedial courses. Connecting individual support with motivational strategies, adaptive AI can simultaneously enhance not only the performance but also the long-term academic commitment or the educational engagement(Sari et al., 2024).

Adaptive AI learning systems, as popular as they may be, remain unknown in terms of how their cumulative effort affects cognitive loads and academic persistence. Most of the previous studies have analyzed these two sides separately, whether in the form of investigating the impact of AI tools on the mental workload or the side left with effects on motivation and perseverance(Taylor et al., 2021).However, the relationship between cognitive load and persistence remains complex since a reduction in the level of mental load may lead to the rise in motivation, but a suitable cognitive task with challenges would also affect persistence (Griskevica & Iltners, 2021).In this paper, an attempt is made to address this gap by considering the impact that adaptive learning systems which utilize AI have on the two of these factors. Being aware of this correlation, educators, instructional designers, and policy-makers will feel that they now know how to employ the AI technologies which can facilitate the process of learning not just by making the process of their experiencing it more efficient but also make sure that students will remain committed to their process of learning. It is through it that this study can be used to offer meaningful wisdom on how technology can promote more sustainable and productive learning conditions in the current education system.

The role of diversity in students concerning the effectiveness of adaptive learning systems built on the basis of AI is the second aspect that must be considered. These variances may be rooted in the preknowledge of learners, their type/ prefs, a cultural background, and exposure to technologies, and may cause learners to react differently to the personalization provided by the AI (Zapata-Rivera & Forsyth, 2022).Even though AI-guided self-paced learning may suit some of these students, other students may require the presence of their teachers or just human contact in general to stay motivated. Moreover, the digital literacy gap can influence the level of how the learners use and use these tools effectively (Van Deursen & van Dijk, 2023).Therefore, the cognitive load and the maintenance of adaptive to the AI component itself should take into account individual differences as far as the influence related to the adaptive AI. This mindset can help to create more inclusive AI systems to ensure the benefits of personalization become accessible to as many learners as possible and so as not to contribute to widening education disparities unknowingly.

In addition to the reduction of the cognitive load and inculcating the concept of perseveres, the role of adaptive artificial intelligence learning systems might also be significant in learning self-regulated skills. Self-regulated learning is a self-regulation in which set goals are followed to monitor and adjust the strategies towards achieving improved outcomes (Zimmerman, 2015).The AI will be able to provide reminders and suggestions on the most sufficient studying habits and provide instant feedback which would then enable the students to be self-regulatory in regards to the learning process (Hadwin et al., 2019).Such systems can encourage both classroom and life-long skills because they develop self-understanding and they force a learner to assess himself/herself. With potentially positive results over time, students engaged with adaptive AI tools could develop stronger problem-solving ability and learn-to-learn without being tightly parented and this could enhance their long-term adherence to the academic system and their general success. The future prospects of such expertise development provides adaptive AI with a future future regarding the production of not only more successful students in their studies but also potentially more successful in the future their professional activities, as well(Bharathyuvaraj & Masilamani, 2024).

Moreover, the technology is very speedy, and adaptive AI learning systems are also developing and they acquire such functions as natural language processing, facial emotions recognition and predictive analysis (Weidman & Baker, 2015).Thanks to these efforts, the systems can learn increasingly more about the needs of students, identifying minor trends in their behavior that may indicate confusion, frustrated students, and/or disengaged students. An example is that emotion-aware

AI could also make adjustments that reflect what the learner may or may not be performing well versus what the learning materials receive insofar as the learner emotional state is more or less favorable perhaps in terms of being more inclusive or responsive with a learning environment (Cloude et al., 2020).As these capabilities grow, the potential impact of the involvements of cognitive burden and academic tenacity also grows. A responsibility therefore, lies in ensuring that pursuant to such developments, such technologies ought to be used in an ethical, transparent and inclusive fashion. The need to balance innovation and responsible application will emerge, to make sure that the teaching potential of adaptive AI will serve education without taking an unreasonable amount of risks and without unforeseen side effects.

1.1 Research objectives

1. To examine the influence of adaptive AI learning systems on students' cognitive load during academic tasks.
2. To investigate the relationship between adaptive AI learning systems and students' academic persistence.
3. To analyze how adaptive AI learning systems simultaneously impact cognitive load and academic persistence across diverse learner groups.

1.2 Problem Statement

Adaptive artificial intelligence technologies are becoming more popular in the modern educational system as a means of individualizing lessons and appealing to learners of all types. The purpose of these systems is to limit non-essential mental strain, or cognitive load, and promote the academic persistence of students, the adherence to the learning objectives of students. Inasmuch as studies indicate that adaptive AI has the potential to enhance learning experiences, few studies have looked at cognitive load and academic persistence in isolation. There is minimal knowledge regarding the interaction of these two factors when it is affected by the AI-based learning environment. This gaps in understanding introduces knowledge blindness as to whether persistence can also be enhanced by reduced cognitive overload due to adaptive AI use or other factors such as learner motivation, background and digital skills dominate. In the absence of definite evidence, educators, policymakers, and technology developers feel hard-pressed in making informed decisions on how to model and utilize these tools. This paper fills this research gap by evaluating the combined effect of adaptive AI learning systems on cognitive loads and academic persistence and the implications of it used in the development of more inclusive, effective, and interesting learning conditions.

1.3 Significance of the Study

The significance of the study is that it touches upon the idea that the adaptive AI-learning systems can help introduce the effect of education on a student by allowing one to keep the equilibrium of their mental workload and not procrastinate in the educational process. In the case of lessons being too tricky or too quick, several of the students struggle and this adds to independent cognitive load, and they are left with neither much probability nor interest to study. The learning process will become less pressure-driven and more engaging because adaptive AI platforms will allow modifying the tempo, content of the lesson and difficulty of the tasks based on the peculiarities of the separate student. Understanding the effect these systems have on the cognitive load and academic persistence, teachers can utilize the AI tools in a more productive way providing the learning outcomes with a boost. The findings of this study can be applied to help educators, school officials, and policymakers establish ways of leveraging the potential of the AI technology to cater to a diverse learner population that may be at risk of failing to master skills and concepts. It can also educate developers to improve the inclusiveness, effectiveness and ethics of AI systems. Overall, the current study could be applied when creating more

reasonable, ethical terms that would not only facilitate students in learning better but also, in motivating them and making them committed to their studies in the long run.

2. Literature Review

Over the last decade, an increased amount of research on how adaptive AI based learning systems can transform education has taken place. Algorithms guarantee the traceability of the progress of individual students in such systems as well as the natural flow of learning materials and, thus such systems can be more personalized compared to traditional instructional approach (Yassin & Mabanja, 2024).Studies have suggested that such a level of individualization is one of the methods that may be implemented to help the students study at the level of their choice, and to maximize overall learning when dealing with online students where teacher engagement may be at a minimum, especially among remote students (Chen et al., 2020).For instance, Carnegie Learning and Knewton are just some of the AI-based tools with which positive results have been reported when it comes to boosting the performance of students in mathematics and science through the delivery of content tailored to them. Such systems, however, with some promising results elsewhere in terms of learning outcomes must persevere with upfront analysis of the outcomes of their intervention in areas beyond grades, and in particular to cognitive processes and areas of motivational evidence of long-term effects on academic achievement

The most salient of the directions of the previous studies could be mentioned the concept of cognitive load or perhaps the pressure of the mental activity to process and realize new information. The theory behind the Cognitive Load by Sweller asserts that when learners are introduced to an excessive level of information, the working memory strains and this leads to reduced learning efficiency (Sweller, 2020).Researchers have found out that adaptive AI systems help to manage such load by dividing content into short and more manageable chunks and providing instant feedback (Patac & Patac Jr, 2025).To depict an example, researches carried on the Intelligent Tutoring systems indicate that when the problems are altered in regard to their issues in real time there would be an enhanced likelihood that the students would stand chances of processing information without the feeling of excessive. This would be used not only to be able to increase knowledge but also to maintain the confidence of the learner.

Adaptive artificial intelligence can also have a positive impact on persistence due to the constant sense of motivation and the investment in a reward of the small success which can also get students interested in it on a daily basis (Zheng & Xiao, 2024).Online classes, e.g., progressive monitoring and gamification (AI based) have been shown to reduce the dropout rate. However, the persistence behavior is not so straightforward and the AI systems may provide the required means of motivating but not all the students will behave similarly. This precedence suggests that the interaction of low cognitive load and high persistence has not been well developed and, thus the need to conduct a research study based on these two variables. Research that is a cross between the theory of cognitive load and motivation models has proven the possibility of encouraging positive learning outcomes as long as the learners receive some motivation under the manageable demand on various facets of their work and with the assistance of some encouragement, a learner has high possibilities of attaining satisfactory learning outcomes (Brockbank, 2025).

2.1 Adaptive AI Learning Systems in Education

Adaptive AI learning systems learning tools that help customize the learning process by automatically changing the content of lessons, their pace of delivery as well as the level of challenge, in order to fit the needs of each learner. These systems monitor the progress of students, pinpointing the

strengths and weaknesses, with the help of data analytics and machine learning algorithms, as well as preparing individual learning paths (Amato et al., 2019).This individualized method has been proven to increase student engagement, understanding, and academic performance specifically in online and blended learning where they may not have much interaction with a teacher (Chen et al., 2022).Case in point: Dream Box, Carnegie Learning and others have shown quantifiable growth in mathematics learning growth through the use of content that is responsive to the abilities of students. Nevertheless, although the present research seems to center on more generally measurable academic outcomes, as with many of the present studies, less research has been conducted on adaptive AI and its impact on other, more profound thinking processes, such as mental effort regulation (cognitive load) and long-term learning commitment (academic persistence). It is noteworthy that this gap could be used to make more practical system designs as the interplay of AI between mental workload and persistence effects is understood. Devoid of these insights, however, the payoffs of adaptive AI can arguably end up only staying on the surface of academic achievements instead of facilitating long-term sustainable and significant learning development over time.

However, over the past few years, adaptive AI has undergone changes and now includes the impressive features of natural language processing (NLP), predictive analytics, and emotion recognition technologies. With these advances, AI systems can react to not only the cognitive performance but also to the emotional state of the learner offering a more comprehensive and considerate learning experience (Vistorte et al., 2024).As another example, an emotion-sensitive AI will be able to identify frustration signs based on the analysis of facial expressions, response rates, or even the typing pace and adjust the instructional contents to avoid disengagement. It is a responsive adjustment that assists in eliminating the issue of cognitive overload, as well as keeping the learner motivated. Evidence indicates that particular systems have the potential to enhance students satisfaction and resilience during learning tasks (Kim, 2025).Nevertheless, the experts warn of excessive dependence on computerized decision-making and specify the associated dangers such as the decline of human supervision, ethical problems, and data security hazards (Williamson et al., 2024).It is necessary due to these concerns, which highlight the importance of healthy integration, with AI acting as a supplement to human educators as opposed to a change of role.

The other important fact recognized about adaptive AI systems is that, they facilitate self-regulated learning, which involves learners developing goals, monitoring performance on them and adjusting strategy to the same (Du, 2025).Adaptive AI tools may have learner control in instructor-mediated tools where the AI may provide real-time feedback, reminders to learn and, perhaps, suggest specific resources to utilize (Winne, 2013). Such features come in handy particularly to students in distance or self-learning courses where some degree of teacher assistance is not always common. The persistence will also be increased due to the use of the AI-based guidance since the guidance increases the student confidence, and the autonomy will promote their continuous commitment to meet their objective in education. It was found that under the timely exchange of feedback and interested suggestions, learners are more likely to control the cognitive load themselves and remain focused over a longer period (Panadero, 2017).However, despite all these benefits, to date, there is no combined research on the impact of an adaptive artificial intelligence system on self-regulated learning and cognitive processes as a complex.

2.2 Cognitive Load and Academic Persistence in AI Learning

According to the Cognitive Load Theory (CLT), human brain is able to process only a limited quantity of data during a short period of time, and once this level is surpassed, it becomes harder to learn. Students can be exhausted, overwhelmed or even confused when too much is presented to them.

Adaptive artificial intelligence learning can significantly contribute to the solution of the problem. These systems are capable of dividing larger concepts into smaller, easier stages, varying difficulty of lessons to the ability of a learner and give swift, specific sorts of feedback. As an example, an AI tutor can accelerate on the side of a better student and decelerate in the case of a struggling student, optimizing the speed according to the needs of the individual. This process can aid in avoidance of mental overload thus learning will not be as stressful and more fun. AI ensures that the students are given sufficient challenge that can help them to concentrate and gain confidence about their skills. Confidence in turn raises the chances of students continuing to work in spite of insurmountable odds rather than throwing in the towel. Students who feel motivated and competent tend to continue pursuing challenging courses even in the long term, and this is necessary in achieving long-term academic life(Harari, 2025).

Academic persistence is a kind of persistence in academics and the possibility to pursue academic-related goals and learning even in hard times. Students in the digital learning environment are affected by different distractions like social media and a lack of face-to-face communication as well as isolation. Such problems are likely to demotivate and even make students drop courses or lose interest. This concern can be partially mitigated with the help of adaptive AI systems that monitor the progress of the students and send prompts, as well as celebrate the minor victories so that a learner understands that they are not wasting their time. As an example, when a student starts lagging behind, the AI may offer additional learning content, simplify the presentation of information or propose some extra practice tasks. Such kind of individual attention is carried out so that students do not feel left out but are always focused on their objectives. In addition, the AI is able to establish the feeling of responsibility, causing students not to forget about deadlines and become more consistent when it comes to studying. This way, adaptive AI does not simply cater to the practical knowledge, but is significant in keeping students motivated and preventing academic dropout. This is quite suggestive in online learning when there might not be a physical classroom structure to rely on, exacerbating persistence (Otto & Raturi, 2024).

In addition to information organization and academic support, an aptitude to work through the learning process is significantly connected to emotional attachment that the learners have to their learning process. The likelihood of discouragement increases due to frustrations, boredom and discouragement on the part of the learners. The AI can detect any of these emotional states that it monitors such patterns as slower reactions, reduced interaction or anything that is used as a signal that the person feels hesitant(Shank et al., 2019). Once detected the AI might suggest a few words of encouragement or small breaks or an alternative learning object to clear the minds of the student. On the other hand, more challenging tasks may also appear in the system when the student exposes confidence and enthusiasm in order to study because the interest was not killed. The mix of this emotional support and intellectual impulse presents a comparison where students do not only experience to be brought to interaction, but also provoked in the longer perspective of time. Emotional connection also builds resilience in that the students are in a position to regain both short and long term distress.

2.3 Research Hypotheses

1. There is a significant relationship between adaptive AI learning system usage and students' perceived cognitive load in digital learning environments.
2. There is a significant influence of cognitive load on students' academic persistence when supported by adaptive AI tools.

3. There are significant differences in academic persistence and cognitive load among students with different demographic characteristics and learning backgrounds when using adaptive AI systems.

3. Methodology

3.1 Research Design

A quantitative research approach was used to develop this study implying that numerical data was acquired and interpreted to learn trends and associations between the variables. The purpose of the study included the investigation of the connection between the use of adaptive AI learning systems and cognitive load and academic persistence of the students. The reason why the quantitative approach was selected is that it permitted the statistical analysis and assisted in verifying whether prominent differences or relations between different factors were present. The study was cross-sectional, which implies that the respondents have been observed at a particular moment but not in the long term. The design was implied to be efficient and practical, especially in case of working with a pool of numerous participants (including several universities). It also enabled cross comparisons across different groups of students e.g. undergraduate and graduate students or students of different fields of study. To make the findings more reliable and easier to analyze a structured questionnaire was adopted to ensure that every participant was asked same questions in the same manner.

3.2 Population

The target population of this study was undergraduate and graduate students enrolled to universities in Pakistan in the city of Punjab. Such students have had to complete at least one course, which explored the use of an adaptive AI learning. These systems encompassed intelligent tutoring systems, adaptive quizzes, personalized learning or other AI-centered systems that customized the learning material based on learning success and requirements by the automated system. Punjab was selected as research context, because it included a variety of public and private universities, which offered a perfect setting in the research to examine varied learners. This group could be deemed as very much relevant since the students who had prior experience of using adaptive AI systems were able to provide important feedback regarding how these technologies had affected the process of their learning. It was both undergraduate and graduate students with an allowance of differences in the experiences at an academic level to be discussed. This enabled the research to establish whether AI based learning systems showed a different level impact as per the stage of education that learners were pursuing.

3.3 Sample Size

In the given research it was set at 300 students, which was considered to be enough to produce statistically significant findings. A sample of this size made the findings more accurate and the conclusion reliable. With 300 participants, not only could one establish relationships between different variables but also among subcategories of students, e.g. between the students attending public universities and those attending private universities, or between undergraduate and graduate students. The sample size was determined basing on the fact that larger sample size reduced sampling errors and the findings could be used more conveniently to designate universal members. Furthermore, this number was chosen because there would be at least some valid data even under the condition that some of the participants may drop out or present incomplete information: there is always a possibility that a sufficient number of responses would be gathered, and it could be analyzed. This was applicable in that the study was able to balance the data collected so that perfection is gotten in terms of accuracy as well as the research process in general to be practical and manageable.

3.4 Sampling Technique

A stratified random sampling technique was used in this study to select participants. The population was divided into different groups, or strata, based on important characteristics such as university type (public or private), academic discipline (science, social sciences, business, etc.), and academic level (undergraduate or graduate). From each stratum, students were randomly selected to take part in the research. This ensured that all major groups within the population were fairly represented in the sample. Stratified random sampling was considered particularly effective in educational research because it reduced the risk of bias that could have occurred if only one type of student group had been included. By ensuring diversity in the sample, the findings of the study were more reflective of the overall population of university students in Punjab who had experienced adaptive AI learning systems. This method strengthened the credibility, reliability, and generalizability of the results.

3.5 Ethical Considerations

This study fulfilled with all the required ethical considerations in order to preserve the rights and well-being of the participants. The subjects were informed about the purpose of the research, that the research is voluntary and he/they has the right to cancel the participation in the process at any time without punishment. A consent of the informed consent was mandatory to participate in the data collection, by every respondent. Confidentiality was also exercised in the hiding of all personal information as anonymous and all the information which was gathered kept safe in a secure manner such that it could not be accessed by other personalities. The questionnaire has been prepared in a way that it did not have sensitive or intrusive questions such that the people in question were not put in an awkward position but at the same time not pressurized. The research was conducted in a truthful and loyal fashion where the result of the study would be described accurately and not manipulated. These ethical considerations have been taken to build a trust and respect among the participants, keep their privacy, and make the research cycle fair and respectful.

4. Data Analysis

The results that were gathered in conducting this research were analyzed through the application of both descriptive and inferential statistics to facilitate accurate interpretation of the results. The responses on the questionnaires received were examined first to ensure completeness and any missing or inconsistent data were duly remedied in a manner that did not compromise the validity of the data. The demographic data of the participants was described using descriptive statistics (frequency, percentage, means, standard deviation) and the results are provided as follows: the participants gender, the academic level (university type, and field of study), and the general experience with adaptive AI learning systems. These descriptive findings gave a preliminary impression of the tendencies in the sample and assisted in the recognition of fundamental trends in the sample. Due to this, inferential statistical analyses were then conducted in order to examine the hypotheses of the study and how there may have been a significant relationship between use of adaptive AI learning systems, cognitive load and academic persistence. Comparative analyses, based on differences between subgroups, including undergraduate and graduate learners and learners at public and private universities, were also conducted, due to which the experience of various learner groups regarding AI-based learning tools could be characterized in more detail. The specific statistical software was used to perform all analyses and appropriate results were displayed in form of tables, charts, and graphs so as to facilitate clear polishing and provision of important meaning to the results.

Table 1: Demographic Characteristics of the Participants (N = 300)

Variable	Categor	Frequency (n)	Percentage (%)
Gender	Male	140	46.7
	Female	160	53.3
Age Group	18–21 years	110	36.7
	22–25 years	130	43.3
	26 years and above	60	20.0
Education Level	Undergraduate	180	60.0
	Graduate	120	40.0
AI Course Experience	1–2 courses	170	56.7
	3–4 courses	90	30.0
	More than 4 courses	40	13.3

The demographic analysis of the participants (N = 300) shows a fairly balanced gender distribution, with 46.7% male and 53.3% female students. Most participants were between 22–25 years old (43.3%), followed by those aged 18–21 years (36.7%) and a smaller proportion aged 26 years and above (20%). In terms of education level, the majority were undergraduate students (60.0%), while 40.0% were graduate students. Regarding experience with AI-based courses, more than half of the respondents (56.7%) had completed 1–2 courses, 30.0% had completed 3–4 courses, and only 13.3% had taken more than 4 courses. These findings indicate that the sample represents a diverse group of university students with varying age ranges, academic levels, and exposure to adaptive AI learning systems, making it suitable for examining the study's research objectives.

Figure 1: Demographic Information

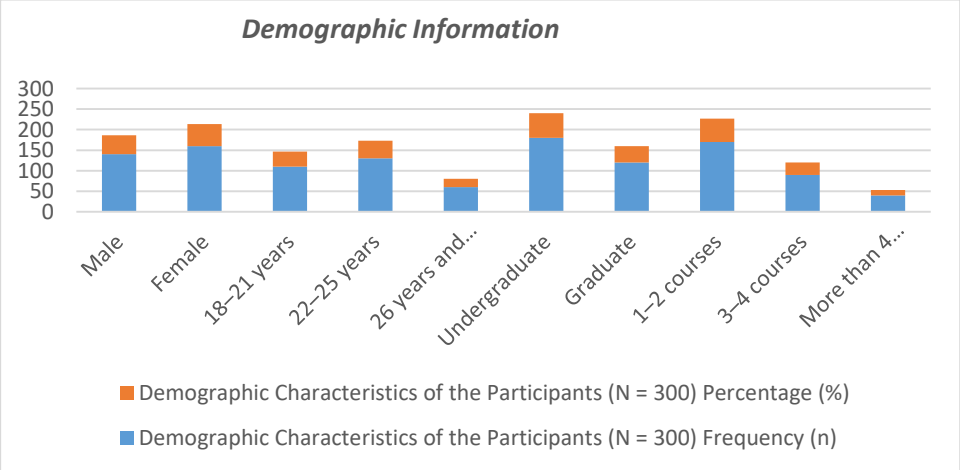


Table 2: Correlation Analysis

Variables	Mean	SD	N	r	p-value
Adaptive AI Learning System Usage	3.85	0.62	300	-0.312	0.000**
Students' Cognitive Load	2.94	0.71	300		

The correlation analysis revealed a significant negative relationship between adaptive AI learning system usage and students' cognitive load (r = -0.312, p = 0.000), indicating that higher use of

adaptive AI tools was associated with lower levels of cognitive load among students. This suggests that when students engaged more with adaptive AI learning systems, which adjust content based on their individual needs and performance, they experienced reduced mental effort in processing and understanding course material. The negative correlation supports the idea that adaptive AI systems can ease cognitive burden by providing personalized learning pathways, targeted feedback, and tailored pacing. The results also confirm the statistical significance of the relationship, as the p-value was less than 0.01, meaning the likelihood of this finding occurring by chance is extremely low. These findings align with previous research emphasizing the role of adaptive learning technologies in simplifying complex learning tasks and enhancing efficiency in knowledge acquisition.

Table 3: Regression Analysis

Predictor Variable	B	SE	β	t	p-value
Constant	1.842	0.215	–	8.563	0.000**
Adaptive AI Learning System Usage	0.456	0.072	0.412	6.333	0.000**

Regression analysis results showed that there was a significant positive correlation between the use of adaptive AI learning systems and academic persistence of students. The fixed value of 1.842 is the indication of the lowest level of academic persistence without the application of the adaptive AI learning systems. This coefficient (B = 0.456) indicates that when the usage of learning systems based on adaptive AI is increased by one unit, the academic persistence also increases by 0.456 units with other things being equal. The effect size is moderate (0.412) that is, adaptive AI learning systems exert a significant effect on the academic persistence. The resulting t-value, 6.333 and the very strong p-value ($p < 0.01$) affirm the power of this relationship. These findings indicate the potential of further use of adaptive AI tools to positively influence the motivation of students to follow their learning missions most probably through personalized helping and lowering the threshold to engage long-term academic performance.

Figure 2: Adaptive AI Learning System Usage and Academic Persistence

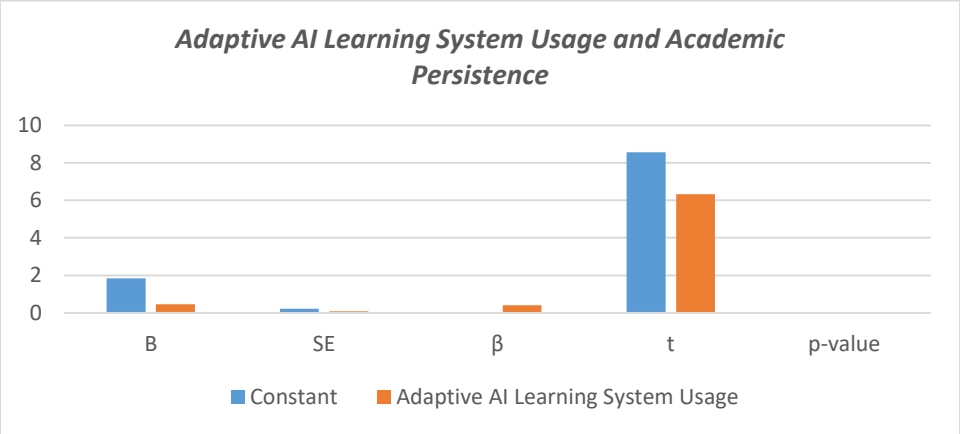
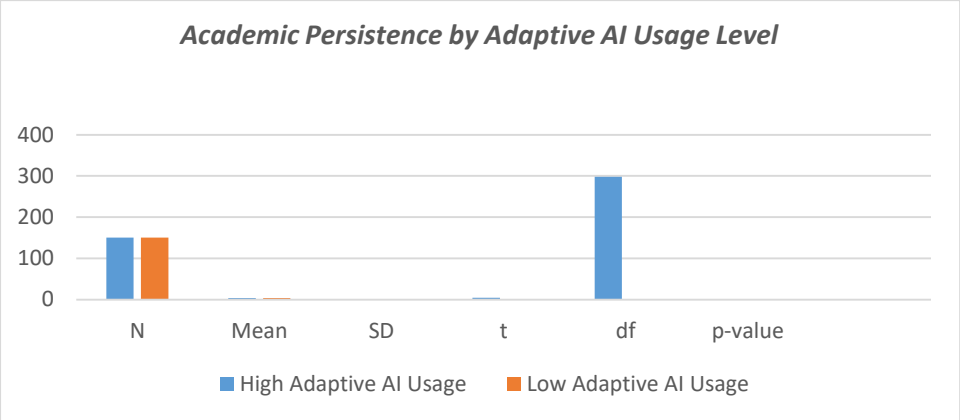


Table 4: Independent Samples t-Test

Group	N	Mean	SD	t	df	p-value
High Adaptive AI Usage	150	3.92	0.58	4.317	298	0.000**
Low Adaptive AI Usage	150	3.54	0.61			

To evaluate statistical significance of differences between the academic persistence of the students with the high level of adaptive AI learning systems usage and low level of usage, we applied independent samples t-test. The difference between the high usage group (M = 3.92; SD = 0.58) and the low usages group (M = 3 54, SD = 0.61) was statistically significant (t (298) = 4.317, p < 0.001). The implication of this is that, students with more frequent access to learning systems that are more practical with adaptive AI to them have a greater level of tenacity in academic practices. The difference in the scores reveals that the application of adaptive AI might involve personalized answers, the provision of certain help and amusing learning paths that would encourage students to continue studying until the end of their application. This supports the hypothesis that adaptive learning technologies could have a major contribution in ensuring the interest and persistence of students remains high and they will ultimately perform better academically.

Figure 3: Academic Persistence by Adaptive AI Usage Level



5. Discussion

The results of the correlation test demonstrated that there is a strong, negative correlation between the usage of adaptive AI learning systems and the cognitive load of the students which postulates that the more students interact with AI tools the lower the mental effort they experience when learning. This goes in line with Cognitive Load Theory because of considering the relevance of instructional design in balancing the processing capacity in the mind of the learner. The decrease in the cognitive load means that adaptive AI systems are capable of making learning content personal, sequencing activities, or offering feedback when needed to address the unique learning needs of a student and consequently avoid learning overloads. These findings are in line with (Kalyuga, 2015),who publishes that technology-aided adaptive learning measures are able to reduce extraneous cognitive load to a modest level as they are adjusting learning to the learning previous knowledge and the learning speed. Here the implication is that AI systems may be used with cognitive support, so the students can learn without having to juggle bits of knowledge that are irrelevant, or inconsistently ordered. This brings to picture the possibility of adaptive AI as more than a content delivery system but also a mechanism of optimizing cognitive efficiency in the online education setting (Sanjalawe et al., 2025).

The regression analysis has shown that the use of the adaptive AI learning systems in higher education was an important predictor of academic persistence as the use of these systems significantly predicted the level of student commitment to their academic program completion. These systems frequently use progress monitoring, individualized feedback, and dynamic adjustment in the level of difficulty, which has the potential to build confidence in the student that she or he can succeed. The finding concurs with the study by (Abeysekera & Dawson, 2015),that the persistence could be improved

through personalized learning environments that will enhance the self-efficacy and academic frustration among students. The willingness of students to study with the help of AI system and maintain their interest in such an educational approach as well as ability to receive sufficient academic support in a timely manner may have contributed to the increased persistence rate seen in the frequent users in this study. Such results can be interpreted to indicate the potential of adaptive AI tools to streamline higher education to prevent dropouts and drive long-term academic performance, particularly in remote or blended learning environments, where self-regulating skills are paramount (Lehikko & Nykänen, 2024).

Independent samples t-test results showed that researchers who used high adaptive AI indicated exorbitant levels of academic persistence compared to those who used it lowly. This promotes the notion that the dynamic application of the AI learning system would promote the creation of more academic mindset and goal centered behavior. It might also be true that the difference between the groups was due to the presence of the AI systems since the individualized and timely learning tracks and interventions, which the AI systems introduce, can keep the learners on track and prevent disengagement. The observation is consistent with that made by Chen et al. (2020), who found that adaptive learning platforms generate a positive impact on students with regard to knowing and attitudes towards learning. The personalization of the platforms precludes the way learning is impeded by over-challenging the learner as well as not stimulating him enough and thus they provide a medium balance that promotes time-long efforts. The results of this study, therefore, suggest that the application of adaptive AI should be considered not just a method that teaches academics, but the tool that brings motivation to students so that they could adhere to their learning intentions. This knowledge has significant implications on instruction design and policy as well as the education policy but to a greater extent in the very environment in which retention and persistence are major concerns.

5.1 Conclusion

This study demonstrated that adaptive AI learning systems can offer excellent enhancements to learning experiences and student learning commitment. The results showed that these kinds of systems allow reducing the mental burden of students, and hence they felt less overwhelmed in understanding the necessary content and focusing on the discipline. Another area where they facilitate the learners is in academic persistence like provision of personalized feedbacks, tracking progress and modifying a content on the individual needs. Students utilized such systems more often the higher was their process-, confidence- level, interest in their studies, and vice versa the less they were used, the less successful were the process-, confidence-, and interest in their studies. In other words, the mere adaptive AI tools may not only be useful in terms of studying the content, but also help the students go further to complete their ultimate goals and avoid demotivation to drop out of school. These observations find their support in the literature in terms of the prior evidence that individual- and patient-adaptive learning interventions can promote performance and motivation. Overall, the study shows a strong possibility of adaptive AI in learning, especially those associated with online/blended learning.

5.2 Recommendations

1. Enhance Availability of Adaptive AI-Based Tools in Universities Adaptive AI learning systems should be made available to all students in universities, whether on a particular course or as a program.
2. Offer Teacher Training- Teachers need to get the right training to ensure that they are able to incorporate the adaptive AI components in the teaching professionally.

3. Adapt AI to Other Disciplines - AI systems cannot be expected to perform at a high rate because of the lack of adaptation based on the type of subject involved.
4. Promote Daily Usage - Students need to be encouraged to use adaptive AI tools as often as possible with the aim of reaping optimized learning outcomes and commitment to academic studies.
5. Monitor Student Progress-Institutions ought to employ artificial intelligence analytics in monitoring and encouraging students who might be lagging behind.
6. Enhance Low Cognitive Load Design = AI platforms should be designed in such a way that they have a clear presentation of information and do not cause mental overload to a learner.
7. Integrate AI and Human Support - Adaptive AI must not displace teacher tutorials but instead, it needs to be used in tandem to produce a balanced learning experience.
8. Perform Frequent Assessment Evaluation at Universities should perform frequent evaluations to determine how well adaptive AI tools are doing and make appropriate adjustments according to feedback and outcomes.

5.3 Future Implications

The results of this research have outlined that adaptive AI learning systems could significantly enhance learning experiences of students, decrease cognitive load, and fortify academic persistence. Universities and policymakers can give these observations in the future to create technology-enriched classrooms in which AI is more than a support mechanism; it is much needed in the learning process. With the ongoing technological advances, it is possible to further individualize the adaptive AI and make the educational process more inclusive and effectual since it will fulfill the needs, abilities, and learning pace of each individual student. Such a strategy might also be used as a means of closing in on students with various academic backgrounds, so that all learners would achieve targeted, personal instructions and help. Also, this data can be used in planning subsequent studies to determine the potential long-term impacts of adapted AI on academic performance, professional preparation, and life-long access to learning skills. Through responsible and ethical use of AI, educational facilities have opportunities to educate students who will be ready to face the future wherein the use of technology is incorporated into all professions, which helps improve academic and career development.

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